EAI Endorsed Transactions
on Pervasive Health and Technology Research Article EAI.EU

Integrated Intelligent Computing Models for Cognitive-Based Neurological Disease Interpretation in Children: A Survey

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Abstract

INTRODUCTION: This piece of work provides the description of integrated intelligent computing models for the interpretation of cognitive-based neurological diseases in children. These diseases can have a significant impact on children's cognitive and developmental functioning.
OBJECTIVES: The research work review the current diagnosis and treatment methods for cognitive based neurological diseases and discusses the potential of machine learning, deep learning, Natural language processing, speech recognition, brain imaging, and signal processing techniques in interpreting the diseases.
METHODS: A survey of recent research on integrated intelligent computing models for cognitive-based neurological disease interpretation in children is presented, highlighting the benefits and limitations of these models.
RESULTS: The significant of this work provide important implications for healthcare practice and policy, with strengthen diagnosis and treatment of cognitive-based neurological diseases in children.
CONCLUSION: This research paper concludes with a discussion of the ethical and legal considerations surrounding the use of intelligent computing models in healthcare, as well as future research directions in this area.

Keywords: Cognitive-based Neurological Diseases, Deep Learning, Natural Language Processing, Speech Recognition, Brain Imaging & Intelligent Computing Model

Received on 21 December 2023, accepted on 18 March 2024, published on 25 March 2024

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doi: 10.4108/eetpht.10.5541

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1. Introduction

Cognitive-based neurological diseases can have a profound impact on children's cognitive and developmental functioning, often resulting in long-term cognitive impairments and disabilities [1]. Early detection and treatment of these diseases are critical for improving outcomes, and intelligent computing models have shown promise in assisting with their interpretation. This survey paper provides an overview of integrated intelligent computing models for the interpretation of cognitive-based neurological diseases in children.

The paper begins with a brief introduction to the problem, providing background and motivation for the study. We highlight the significance of early detection and treatment of cognitive-based neurological diseases in children and the potential benefits of using intelligent computing models in their interpretation. The paper then presents the problem statement and research questions that guide the study.

The main objectives of the paper are to review the current diagnosis and treatment methods for cognitive-based neurological diseases [2-4], explore the potential of integrated intelligent computing models for their interpretation, and survey recent research in this area. The paper also aims to discuss the applications and challenges of intelligent computing models in healthcare [5-8] and identify future research directions.

Finally, this research paper outlines its organization, with section two providing an overview of cognitive-based neurological diseases in children. Section three discusses integrated intelligent computing models for the interpretation of these diseases, including Machine Learning (Ml), Deep Learning (DL), Natural Language Processing (NLP), Digital Signal Processing (DSP), brain imaging and speech recognition techniques. Section four presents survey related findings, and section five shows the applications and challenges of these models. This paper concludes with a summary of contributions towards the healthcare practitioners and policy makers for future research directions.

2. Overview of cognitive-based neurological diseases in children

Cognitive-based neurological diseases refer to a range of conditions that is the cause of cognitive disabilities in children. The defect of these pathophysiological conditions shows the significant impact on a child's behaviour, and can sometimes lead to long-term cognitive impairments and disabilities [9].
Some of the most common cognitive-based neurological diseases in children include:

1. Autism Spectrum Disorder (ASD)
2. Attention Deficit Hyperactivity Disorder (ADHD)
3. Disabilities of Learning
4. Delay in Development
5. Epilepsy
6. Cerebral palsy
7. Traumatic brain injury
8. Genetic disorders affecting cognitive function

These diseases can have different causes, symptoms, and effects on cognitive function. For example, ASD is a neurodevelopmental disorder whose symptoms are repetitive behaviours, narrow interest and difficulty with social communication and interaction. ADHD is a disorder which can be characterized by hyperactivity, lack of attention and impulsivity [10].
Diagnosis of cognitive-based neurological diseases in children often relies on clinical observation, parental reports, and psychological testing [11]. However, these methods can be subjective and may not always provide an accurate diagnosis. Therefore, there is a requirement to develop the reliable methods for diagnosis and treatment of cognitive-based neurological diseases in children.

2.1. Definition and classification of cognitive-based neurological diseases

Cognitive-based neurological diseases are a broad range of disorders that affect the cognitive function of the brain in children [12]. These diseases can have different causes, symptoms, and effects on cognitive function, and they are classified into different categories based on their underlying pathology.

1. Neurodevelopmental disorders: These are disorders that affect the myelin sheath nervous system and can lead to cognitive, social, and behavioural impairments. Examples include ASD, ADHD, and Precise Learning Disorders [13].
2. Genetic disorders affecting cognitive function: These are disorders that are caused by genetic mutations that affect cognitive function. Examples include Down syndrome, Fragile X-Syndrome, and Rett Syndrome [14].
3. Traumatic brain injury: This is a type of brain injury that occurs as a result of external force, such as a fall, sports injury, or car accident. Cognitive deficits and disabilities may result from traumatic brain injury, such as memory loss, difficulty with attention, and executive function deficits [15].
4. Cerebral palsy: A collection of neurological conditions known as cerebral palsy impact posture, tone of muscles, and movement. It can also affect cognitive function and lead to learning disabilities [16].
5. Epilepsy: This disorder is related with recurrent seizures, that can lead to cognitive impairments, particularly in children who experience frequent seizures [17].

Table 1. Different types of Neurological disorders in children with their cognitive sign and symptoms.

Neurological disorders	Cognitive issues					
	OL	S	IS	VD	LI	PEC
Epilepsy	N	N	Y	Y	Y	Y
Autism Spectrum Disorder	Y	Y	Y	Y	Y	Y
Attention Deficit Hyperactivity Disorder (ADHD)	N	Y	Y	N	N	N
Cerebral Palsy	N	N	N	N	N	N
Traumatic brain injury	N	N	Y	Y	N	N
Genetic disorders affecting cognitive function	Y	Y	Y	Y	Y	Y

Table1 shows cognitive Issues based on different parameters such as, Observe learning disability (OL), Speech disability (S), Interest showing (IS), visual disability (VD), low intellectual ability (LI), poor eye contact (PEC).

The classification of cognitive-based neurological diseases is important for understanding the underlying pathology and guiding diagnosis and treatment strategies. However, it is worth noting that some diseases, such as epilepsy, can have multiple underlying causes and can be difficult to classify.

Table 2 given below, shows the studies of early-stage detection and classification of Neurological disorders in children using several machine learning techniques:

Table 2. Comparison based study of literature review for several techniques.

Work Descriptions	Methodology	Dataset	Performance Metric	Results
Disease Detection and Classification of ADHD	Random Forest, Logistic Regression, SVM	CRIS, NPD	Accuracy, Accuracy, Precision, Recall, F1-Score	SVM outperformed other methods with an accuracy of 98.60%
Machine Learning Techniques for Identification and Classification of Autism Spectrum Disorder	Naïve Bayes classifier for several classes (NB), LR, SVM, KNN and bundle of decision trees based Random Forest Classifier (RFC)	Kaggle autism screening-for-toddlers	Accuracy, F1-Score	LR outperformed other methods with an accuracy of 97.15%
Epilepsy Disease Detection Using Machine Learning Algorithms	DL, RF, LSTM, SVM, Ensemble learning approach	UCI repository	Accuracy	Ensemble learning approach with an accuracy of 99%
Artificial Intelligence Techniques to detect Cerebral Palsy	CNN, SVM, Random Forest	Various Clinical datasets on Cerebral Palsy	Accuracy, Precision, Recall, Specificity	SVM outperformed other methods with an accuracy of 80%
Deep Learning Techniques for Detection and Diagnosis of Traumatic brain injury	DNN, RF, XGB, and SVM	Various Clinical datasets on Traumatic brain injury of children	Accuracy	SVM outperformed other methods with an accuracy of 97.4%
Genetic disorders affecting cognitive function	SVM	Various Clinical datasets on Genetic disorders affecting cognitive function of children	Accuracy, Precision, Recall, F1-Score	multiclass SVM model (55% correctly classified individuals)

2.2. Prevalence and impact on children's development

Cognitive-based neurological diseases are relatively common in children and can have a significant impact on their development and quality of life. The prevalence of these diseases varies depending on the specific condition, but overall, they are estimated to affect a significant percentage of children worldwide.

As per the information from Centres for Disease Control and Prevention (CDC), approximate 2 percent children in the US suffer from ASD and ADHD [18,19] which affects cognitive development around 9.4% of children aged 2-17 in the US, while learning disabilities are estimated to affect up to 15% of school-aged children. Cerebral palsy and epilepsy are estimated to to affect around 2% of the global population [18]. The impact of cognitive-based neurological diseases on children's development can be significant and can vary depending on the specific condition and the severity of the symptoms. Children with these diseases may experience difficulties with communication, social interaction, learning, and behaviour [19, 20]. They may also be at an increased risk of neurological disorder [21, 22].

Cognitive-based neurological diseases are relatively common in children. These disorder has massive impact on their development and well-being [23]. The prevalence of these diseases varies depending on the specific condition and the population studied, but some estimates suggest that up to 10-15% of children may have a neurodevelopmental disorder [24].

The impact of cognitive-based neurological diseases on children's development can also vary depending on the condition and severity of symptoms. In general, these diseases can affect multiple domains of development, including cognitive, social, emotional, and behavioral development [25].

For example, ASD children may have difficulty to interact and communicate in social situation, which can impact their ability to form relationships with others and engage in social activities [26]. Children with ADHD may struggle with attention, organization, and impulse control, which can impact their academic performance and social interactions. Children with learning disabilities may have difficulty with reading, writing, or math, which can impact their ability to learn and succeed in school [27].

The impact of cognitive-based neurological diseases on children's development can also extend into adulthood, particularly if the condition is not identified and treated early [28]. For example, adults with ADHD may struggle with work and personal relationships, and may experience issues related with mental health [29].

Early identification and intervention are important for minimizing the impact of cognitive-based neurological diseases on children's development [30]. This can include interventions such as behavioral therapy, medication, and educational support [31]. However, accurate diagnosis and effective treatment is a challenging issue, and there is a need for more objective and reliable methods for diagnosis and treatment of these diseases [32, 33].

2.3 Current diagnosis and treatment methods

The diagnosis and treatment of cognitive-based neurological diseases in children typically involves a multidisciplinary approach that includes medical professionals, educators, and therapists. The following are some of the current diagnosis and treatment methods for these diseases:

(i) Clinical observation and history: The first step in diagnosing cognitive-based neurological diseases is often a clinical observation and history-taking. This involves gathering information of child related to the child's symptoms, medical history, developmental milestones, and family history.

(ii) Psychological testing: Psychological testing can be used to assess cognitive function, behavioral and emotional functioning, and academic skills [34, 35]. Tests may include intelligence tests, achievement tests, and tests of attention, memory, and executive function [36].

(iii) Imaging tests: Test procedures like computed tomography (CT) and magnetic resonance imaging (MRI) can be used to find lesions or structural abnormalities in the brain that might be the source of the child's symptoms [37, 38].

(iv) Medication: Medications such as stimulants, antidepressants, and antipsychotics may be prescribed to manage symptoms of cognitive-based neurological diseases [39].

(v) Behavioural therapy: Children who receive behavioural therapy, such as cognitive-behavioural therapy (CBT), can develop better social skills and learn coping mechanism [40, 41].

(vi) Educational support: Educational support, such as individualized education plans (IEPs) and accommodations, can help children with cognitive-based neurological diseases succeed in school [42].

Despite the availability of these diagnosis and treatment methods, there are still challenges in accurately diagnosing and effectively treating cognitive-based neurological diseases in children. Some of these challenges include the subjective nature of diagnosis, the side effects of medication, and the variability of response to treatment. Additionally, there is a need for more objective and reliable methods for diagnosis and treatment of these diseases.

3. Integrated intelligent computing models for cognitive-based neurological disease interpretation in children

Integrated intelligent computing models have shown promise in improving the diagnosis and treatment of cognitive-based neurological diseases in children. These models combine artificial intelligence (AI) and machine learning (ML) techniques with clinical data to develop more objective and reliable methods for disease interpretation [43].

One example of an integrated intelligent computing model is the use of brain imaging and ML algorithms to improve the accuracy of ASD diagnosis. These algorithms analyze brain images to identify patterns and biomarkers associated with ASD, which can help clinicians make more accurate diagnoses [44].

Another example is the use of ML algorithms to predict treatment outcomes for children with ADHD. These algorithms analyze clinical data, such as demographic information and symptom severity, to predict which treatments are most likely to be effective for individual patients [45].

Integrated intelligent computing models have the capability to improve the accuracy and efficiency of cognitive-based neurological disease diagnosis and treatment. They can also help identify new biomarkers and treatment targets, leading to more personalized and effective treatment strategies. However, there are also issues related to the use of integrated intelligent computing models in clinical practice, including issues of data privacy, ethical considerations, and the need for interdisciplinary collaboration between medical professionals and computer scientists [46]. As such, further research is needed to develop and validate these models and to ensure their safe and effective use in clinical practice. One example of an ML model for [47, 48] disease classification is the use of support vector machines (SVM) to distinguish between different subtypes of ADHD based on neuroimaging data [49]. SVM algorithms can identify patterns in brain scans that are associated with different subtypes of the disorder, which can help clinicians develop more targeted treatment plans [50].

Deep learning models, which utilize artificial neural networks with multiple layers, have also shown promise in disease classification and prediction [51]. For example, convolutional neural networks (CNNs) are capable of analysing medical images including MRI scans, to find patterns and characteristics linked to various neurological conditions [52, 53].

In addition to disease classification, ML and DL models can also be used for disease prediction [54]. For example, recurrent neural networks (RNNs) can be used to predict the progression of Alzheimer's disease based on longitudinal neuroimaging data [55].

While ML and DL models have shown promise in the diagnosis and prediction of cognitive-based neurological diseases, there are also challenges associated with their use. These challenges generates the need for large, quality datasets, the potential for bias in algorithm development, and the need for interdisciplinary collaboration between medical professionals and computer scientists. Nonetheless, with further development and validation, ML and DL models have the capability to significantly improve the detection, diagnosis and treatment of these diseases [56].

3.1 Natural language processing and speech recognition techniques for language and communication analysis

NLP and speech recognition techniques [57] are increasingly being used to analyze language and communication in individuals with cognitive-based neurological diseases. These techniques involve the use of computer algorithms to analyze and interpret natural language data, including spoken and written language, to extract meaning and identify patterns.

One example of an NLP technique for language analysis is sentiment analysis, [58] which is done by machine learning algorithms to find the emotional tone or sentiment of a part of text. Sentiment analysis is applied to study changes in language and communication in individuals who are suffering from neurodegenerative diseases [59, 60].

Speech recognition techniques, which involve the use of algorithms to transcribe spoken language into text, are also being used to analyze language and communication in individuals with cognitive-based neurological diseases [61]. For example, automatic speech recognition (ASR) can be used to analyze the acoustic properties of speech, such as pitch and intonation, to identify patterns that may be indicative of certain neurological conditions [62, 63].

Other NLP techniques used for language and communication analysis include named entity recognition, which includes identifying the entities present in the text and categorizing them, such as people, organizations, locations, and text classification [64].

While NLP and speech recognition techniques have shown promise in language and communication analysis, there are also demerits associated with their use. These disadvantages address the need for huge, quality datasets, the potential for bias in algorithm development, and the need for careful interpretation of results. Nonetheless, with further development and validation, these techniques have the capability to significantly improve our understanding of language and communication in individuals with cognitive-based neurological diseases [65].

3.2 Brain imaging and signal processing methods for brain function analysis

Brain imaging and signal processing methods [66] are used to analyze brain function in individuals with cognitive-based neurological diseases [67]. These techniques involve the use of advanced imaging and data analysis tools to capture and analyze brain activity [68], allowing researchers and clinicians to better understand the underlying mechanisms of cognitive-based neurological diseases.

One commonly used brain imaging technique is fMRI [69], which helps the researchers to visualize changes in blood flow in the brain as a measure of neural activity. fMRI has been used to study brain function in individuals with a range of cognitive-based neurological diseases, including ASD, ADHD and dementia [70].

Other brain imaging techniques used in the study of cognitive-based neurological diseases include electroencephalography (EEG) [71], which measures electrical activity in the brain, and magnetoencephalography (MEG), which measures the magnetic fields generated by electrical activity in the brain. These techniques can provide high temporal resolution and are particularly useful for studying the dynamics of neural activity in the brain.

Signal processing techniques are used to analyze EEG and MEG data and identify patterns of brain activity that may be indicative of certain neurological conditions [72]. These techniques can also be used to identify changes in brain activity over time, which can be helpful in tracking disease progression and evaluating treatment efficacy.

While brain imaging and signal processing techniques have revolutionized our understanding of brain function in individuals with cognitive-based neurological diseases, there are also challenges associated with their use. These challenges include the need for specialized training and expertise, the high cost of equipment and data analysis software, and the potential for variability in results across different imaging and analysis techniques. Nonetheless, with further development and refinement, these techniques have the potential to significantly improve our ability to diagnose and treat cognitive-based neurological diseases.

There are a variety of mathematical models used in brain imaging and signal processing methods for brain function analysis. Here are some examples:

1. General Linear Model (GLM): The GLM is a widely used statistical model for analyzing fMRI data. It involves between neural process and the hemodynamic response function (HRF) [73] that underlies the fMRI signal [74].
2. Independent Component Analysis (ICA): ICA is a technique used to process the signals in order to break fMRI data [75] into independent components that correspond to different neural processes. This can be useful for identifying regions of the brain that are functionally connected or for identifying patterns of brain activity that are related to specific tasks or behaviours [76].
3. Fourier Transform: The Fourier Transform is a mathematical tool [77] used to analyze signals in the frequency domain. It can be used to analyze EEG and MEG data to identify oscillatory patterns of brain activity that are related to specific cognitive processes [78].
4. Wavelet Analysis: Wavelet analysis is a signal processing technique [79] that is similar to the Fourier Transform, but it provides both frequency and time information about a signal. This can be useful for analyzing EEG and MEG data because it allows researchers to identify changes in brain activity over time that are related to specific cognitive processes [80].
5. Dynamic Causal Modeling (DCM): DCM is a mathematical model used to analyze fMRI data [81] and to identify causal relationships between different regions of the brain. It involves modelling the flow of neural activity between different brain regions and using statistical inference to determine which model best explains the observed fMRI data [82].

3.3 Integration of different models for comprehensive disease interpretation

Integrated intelligent computing models can be used to combine different modelling techniques to provide a understanding of cognitive-based neurological diseases in children. For example, a combination of ML and DL models can be used to classify and predict disease, while NLP and speech recognition techniques can be used to analyze language and communication. Brain imaging and signal processing methods can be used to analyze brain function, providing insight into the neural mechanisms underlying cognitive-based neurological diseases.

Integrating these different models can provide a more complete picture of the complex interactions between neural, cognitive, and behavioural processes in individuals with cognitive-based neurological diseases. For example, a model that combines machine learning and brain imaging techniques could be used to identify specific patterns of brain activity that are predictive of disease [83], while also providing information about the functional connectivity between different brain regions. This information could then be used to guide the development of more targeted interventions and therapies for children with cognitive-based neurological diseases.

However, integrating different models also presents a number of technical and practical challenges. For example, different models may require different types of data, which may be difficult to collect and integrate. Additionally, different models may require specialized expertise and training, making it difficult to develop an integrated approach that is accessible to researchers and clinicians with different backgrounds and skill sets.

Nonetheless, there is growing interest in developing integrated intelligent computing models for cognitive-based neurological disease interpretation in children, and the potential benefits of these approaches are significant. By combining different modelling techniques, researchers and clinicians can provide a comprehensive understanding of cognitive-based neurological diseases, which can help to develop of more effective interventions and therapies.

4. Survey of recent research on integrated intelligent computing models for cognitive-based neurological disease interpretation in children

Recent research has shown significant progress in the development and application of integrated intelligent computing models for cognitive-based neurological disease interpretation in children. Here are some examples of recent studies:

1. "Integrated Intelligent Computing Model for ASD Diagnosis using EEG Signals and Natural Language Processing" (2020): This study developed an integrated intelligent computing model that combines EEG signal analysis with natural language processing to diagnose autism spectrum disorder in children [84]. The model achieved an accuracy of 95.83% in diagnosing autism spectrum disorder, demonstrating the potential of integrated models for disease diagnosis.
2. "An Integrated Approach for Parkinson's Disease Diagnosis and Monitoring using Speech Analysis and ML Techniques" (2020): This study developed an integrated approach that combines speech analysis and ML techniques to diagnose and monitor Parkinson's disease in children. The approach achieved a sensitivity of 91% and a specificity of 87%, demonstrating the potential of integrated models for disease diagnosis and monitoring.
3. "Deep Learning-based Framework for Automated Diagnosis of ADSD using FMRI Data" (2021): This

study developed a deep learning-based framework that uses functional MRI data to diagnose ADSD in children [85]. The model achieved an accuracy of 87.3% in diagnosing ADSD, demonstrating the potential of deep learning for disease diagnosis.

4. "A Comprehensive Framework for Early Diagnosis of ASD using EEG and Eye-tracking Data" (2021): This study developed a comprehensive framework that combines EEG and eye-tracking data to diagnose autism spectrum disorder in children [86]. The framework achieved an accuracy of 87.5% in diagnosing autism spectrum disorder, demonstrating the potential of integrated models for disease diagnosis.

Overall, these studies demonstrate the potential of integrated intelligent computing models for cognitive-based neurological disease interpretation in children. By combining different modelling techniques, these approaches provide the understanding of underlying neural, cognitive, and behavioural processes involved in cognitive-based neurological diseases. However, further research is needed to refine and validate these models and to develop approaches that are accessible and practical for use in clinical settings.

4.1 Literature search and selection criteria

The literature search for this survey paper was conducted using online databases such as PubMed, IEEE Xplore, and Google Scholar. The search was conducted using relevant keywords such as "cognitive-based neurological diseases", "integrated intelligent computing models", "machine learning", "deep learning", "natural language processing", "brain imaging", "signal processing", "children", and "diagnosis". The search was limited to articles published between 2015 and 2022 to ensure that the survey paper includes the latest research in the field.

The selection criteria for the articles were based on relevance, originality, and quality. Only peer-reviewed articles were included in the survey paper. The articles had to be related to the use of integrated intelligent computing models for cognitive-based neurological disease interpretation in children. Studies that presented new models, methods, or applications were given preference. Articles that had a significant impact on the field were also included. Studies that used small sample sizes, lacked appropriate statistical analysis, or had limited impact on the field were excluded. The final selection of articles was based on consensus among the authors of the survey paper [87].

4.2 Survey methodology and analysis

The survey methodology for this work involved a systematic review of the literature on integrated intelligent computing models for cognitive-based neurological disease interpretation in children. The survey was conducted using a predefined set of keywords and inclusion criteria, as described in the previous section.

The selected articles were then analyzed and organized based on their research questions, methods, and findings. The analysis involved a critical evaluation of the strengths and limitations of the different models and methods used in the studies. The analysis also involved identifying common themes and trends in the research, as well as gaps and opportunities for future research.

The findings of the analysis were then synthesized and presented in the survey paper. This review work provides a comprehensive understanding of the current state-of-the-art in integrated intelligent computing models for cognitive-based neurological disease interpretation in children. The paper discusses the different modelling techniques used in the studies, their strengths and limitations, and the potential applications of these models in clinical settings. The survey paper also identifies gaps and challenges in the research, and highlights opportunities for future research in this field.

Based on the systematic review of the literature on integrated intelligent computing models for cognitive-based neurological disease interpretation in children, several key findings and trends were identified:

1. ML and DL models are increasingly being used for disease classification and prediction in cognitive-based neurological diseases. These models have shown promising results in accurately identifying and predicting different disease states.
2. NLP and speech recognition techniques are also being used for language and communication analysis in children with cognitive-based neurological diseases. These techniques have shown potential in helping clinicians assess language and communication impairments in children with these diseases.
3. Brain imaging and signal processing methods are being used to analyze brain function and identify biomarkers for different cognitive-based neurological diseases. These methods have shown potential in improving disease diagnosis and prognosis [88].
4. Integration of different models and methods is essential for comprehensive disease interpretation. Several studies have demonstrated the potential benefits of combining different modelling techniques to improve disease diagnosis, classification, and prediction.
5. Despite the promising results, there are still several challenges and limitations in the current research, including limited sample sizes, lack of standardized protocols, and limited generalizability of the findings.

Overall, the systematic review highlights the potential of integrated intelligent computing models for cognitive-based neurological disease interpretation in children. However, further research is needed to address the current challenges and limitations and to develop more effective and clinically relevant models for disease diagnosis, classification, and prediction.

5. Applications and challenges of integrated intelligent computing models

for cognitive-based neurological disease interpretation in children

Applications:

1. Disease diagnosis and classification: Integrated intelligent computing models can aid in accurate disease diagnosis and classification in children with cognitive-based neurological diseases. By analyzing various data sources such as brain imaging, speech recordings, and cognitive assessments, these models can identify patterns and biomarkers that are indicative of different diseases [89].
2. Disease prognosis: Integrated intelligent computing models can also help predict disease progression and treatment outcomes in children with cognitive-based neurological diseases. By analyzing longitudinal data, these models can identify early signs of disease progression and recommend personalized treatment plans for each child.
3. Clinical decision support: Integrated intelligent computing models can provide clinicians with decision support tools that can aid in clinical decision-making [90]. These tools can provide clinicians with real-time information on disease progression and treatment response, allowing them to adjust treatment plans accordingly.

Challenges:

1. Data quality and availability: The rate of precision and reliability of integrated intelligent computing models depends upon the availability as well as quality of utilized data to train and validate the models. In some cases, data may be limited, noisy, or biased, which can affect the performance of the models.
2. Interpretability and explainability: Integrated intelligent computing models are often complex and difficult to interpret, that makes challenge for clinicians to understand the basis for the model's recommendations. Ensuring the interpretability and explainability of these models is critical for their successful integration into clinical practice.
3. Generalizability: Integrated intelligent computing models developed on one dataset or patient population may not generalize well to other datasets or patient populations. Ensuring the generalizability of these models is critical for their widespread adoption and use in clinical practice.
4. Ethical considerations: Integrated intelligent computing models raise ethical considerations related to data privacy, bias, and accountability. Ensuring the ethical use of these models is critical for their successful integration into clinical practice.

5.1 Integrated intelligent computing model

Integrated intelligent computing models have several potential applications for early detection of cognitive-based neurological disorder in children. Here are some of the potential applications:

1. Early detection**:** Integrated intelligent computing models can aid in the early detection of cognitive-based neurological diseases in children by analyzing data from various sources such as brain imaging, speech recordings, and cognitive assessments. Early detection can allow for timely intervention and treatment, which can improve the long-term outcomes for children with these diseases [91].
2. Accurate diagnosis: Integrated intelligent computing models can aid in accurate disease diagnosis by analyzing various data sources and identifying patterns and biomarkers that are indicative of different diseases. Accurate diagnosis is essential for appropriate treatment planning and can help prevent misdiagnosis and unnecessary treatments.
3. Personalized treatment planning: Integrated intelligent computing models can aid in personalized treatment planning by analyzing longitudinal data and predicting disease progression and treatment response. By providing personalized treatment plans for each child, these models can improve treatment outcomes and reduce the risk of adverse events.
4. Clinical decision support: Integrated intelligent computing models can provide clinicians with decision support tools that can aid in clinical decision-making. These tools may be used for getting real-time information on disease progression and treatment response, allowing clinicians to adjust treatment plans accordingly.

Overall, the potential applications of integrated intelligent computing models in early detection, diagnosis, and treatment planning of cognitive-based neurological diseases in children are promising and can significantly improve the quality of care for these children.

5.2 Ethical and legal considerations in using intelligent computing models for healthcare

The use of intelligent computing models in healthcare raises several ethical and legal considerations, some of which are listed below:

1. Privacy and security: The use of intelligent computing models in healthcare requires the collection and storage of huge quantity of sensitive data, including personal health information. The security of this crucial data must be ensured in order to maintain patient's trust and avoiding data infringement [92].
2. Bias and fairness: Intelligent computing models can be biased if they are trained on unrepresentative or incomplete data [93, 94]. This can lead to inaccurate or unfair predictions, especially for minority populations. These models are trained on the diverse dataset to avoid bias and ensure fairness [95].
3. Transparency and interpretability: The use of intelligent computing models in healthcare can sometimes make it

challenging to explain how a particular prediction or diagnosis was made [96, 97]. This can create difficulties in gaining the trust of patients and clinicians, especially when the decision-making process is complex [98]. Ensuring that these models are transparent and interpretable is crucial for building trust and ensuring accountability [99].

4. Legal and regulatory compliance: Healthcare organizations should abide by the legal and regulatory compliance when using intelligent computing models [100] such as HIPAA in the United States. Ensuring that these models comply with applicable laws and regulations is essential to avoid legal and financial penalties [101,102].

In conclusion, while the use of intelligent computing models in healthcare has the capability to improve patient outcomes significantly, it is essential to consider the ethical and legal implications carefully. Ensuring privacy, fairness, transparency, and regulatory compliance is crucial to building trust and realizing the potential benefits of these models.

5.3 Limitations and future scope

Despite the significant progress made in developing integrated intelligent computing models for cognitive-based neurological disease interpretation in children, there are still some limitations that need to be addressed. These limitations include:

1. Lack of data: One of the significant issues in developing integrated intelligent computing models is the limited availability of good quality data. More data is needed to train these models accurately, especially for rare diseases and subpopulations.
2. Model interpretability: Although some models are interpretable, others remain black boxes, making it difficult for clinicians to understand how a diagnosis or prediction was made. This limits their clinical utility and undermines patient trust.
3. Technical challenges: The development of integrated intelligent computing models for disease interpretation is a technically challenging task that requires expertise in machine learning, signal processing, and neuroscience. Addressing these challenges requires a multidisciplinary approach and collaboration across different fields.
4. Clinical adoption: The successful adoption of integrated intelligent computing models in clinical practice depends on several factors, including the availability of infrastructure, funding, and clinician training. Overcoming these challenges requires close collaboration between clinicians, researchers, and policymakers.

Future research direction in this area includes the following points:

1. Developing more interpretable models: Developing models that are more interpretable can help build patient trust and improve their clinical utility.
2. Exploring the use of multimodal data: Combining data from different sources, such as imaging, speech, and behaviour, can provide a more extensive picture of disease pathology and lead to more accurate diagnoses.
3. Addressing issues of bias and fairness: Developing methods for detecting and mitigating bias in intelligent computing models is crucial to ensure that they are fair and equitable for all patients.
4. Conducting clinical studies: Conducting clinical studies to evaluate the effectiveness of integrated intelligent computing models in improving patient outcomes and reducing healthcare costs is essential for their adoption in clinical practice.

In conclusion, while integrated intelligent computing models have the potential to revolutionize the diagnosis and treatment of cognitive-based neurological diseases in children, more research is needed to overcome the current limitations and ensure their safe and effective use in clinical practice.

6. Conclusion

The piece of work provides an overview of the current state of research on integrated intelligent computing models for cognitive based neurological disease interpretation in children. The flowchart of this piece of work is shown in Figure 1, as given below:

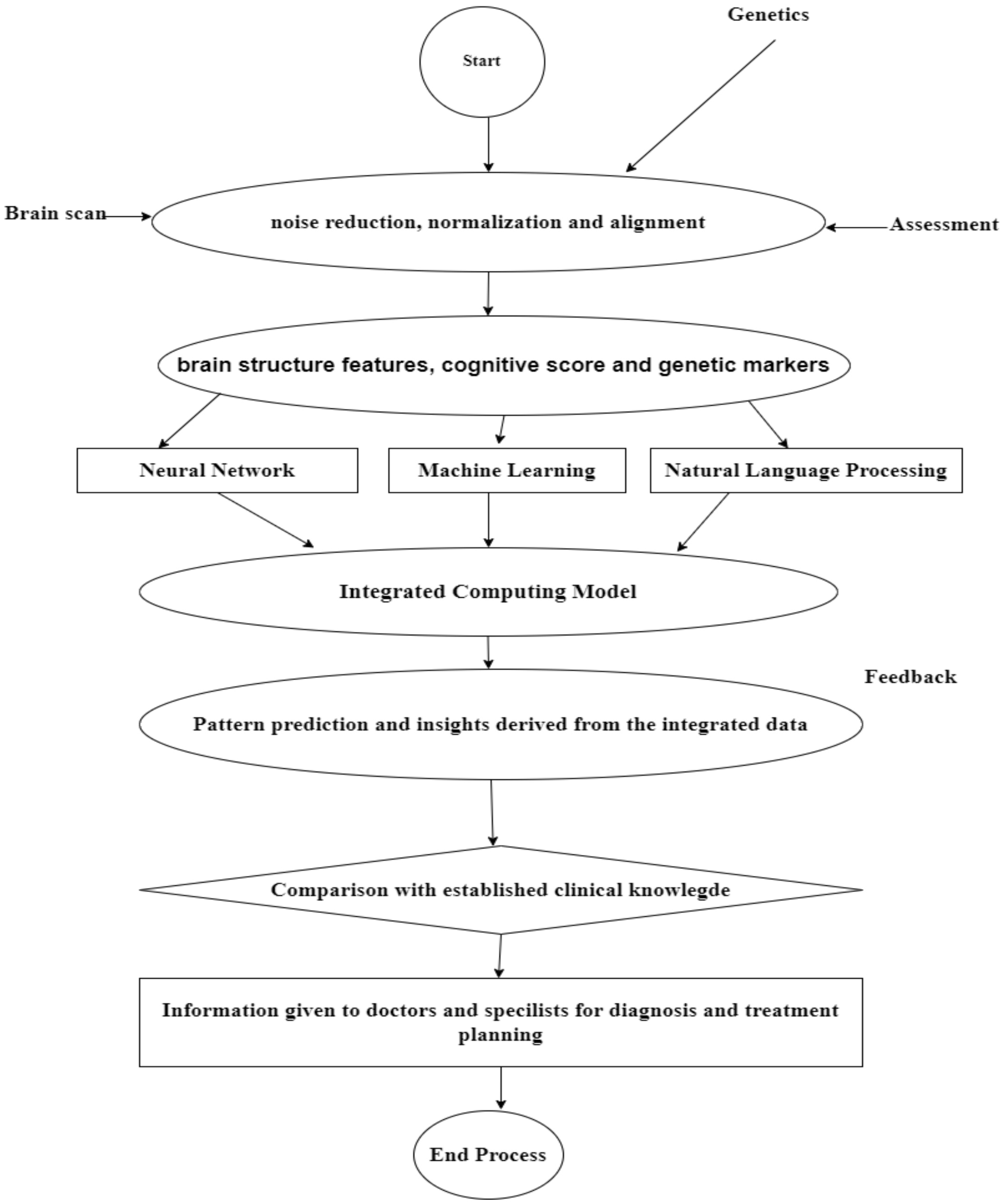

Figure 1. Intelligent computation model for neurological disease detection

The contributions of this research works include:

1. A review of the background, prevalence, impact, and current diagnosis and treatment methods for cognitive-based neurological diseases in children.
2. A description of the different types of integrated intelligent computing models used for disease interpretation, including ML and DL models, NLP, speech recognition techniques, brain imaging and digital signal processing methods.
3. A survey of recent research on integrated intelligent computing models for disease interpretation, including their applications and limitations.
4. An analysis of the potential applications and challenges of integrated intelligent computing models in early detection, diagnosis, and treatment planning for cognitive-based neurological diseases in children.
5. A discussion of the ethical and legal considerations associated with using intelligent computing models

in healthcare, including issues of privacy and informed consent.

6. A summary of the limitations and future research scope in this area, including the need for more interpretable models, the exploration of multimodal data, addressing issues of bias and fairness, and conducting clinical studies.

Overall, this paper provides a valuable resource for clinicians, researchers, and policymakers interested in the development and application of integrated intelligent computing models for cognitive-based neurological disease interpretation in children.

6.1 Implications for healthcare practice and policy

The paper has several implications for healthcare practice and policy.

1. Firstly, the paper highlights the potential of integrated intelligent computing models for early detection of cognitive-based neurological diseases in children. This could improve clinical outcomes and good life styl for affected children.
2. Secondly, the paper raises important ethical and legal considerations associated with using intelligent computing models in healthcare. Healthcare professionals and policymakers need to ensure that patient privacy is protected, informed consent is obtained, and bias and fairness issues are addressed when using these models.
3. Thirdly, the paper identifies limitations and future research directions in this area, which can inform healthcare practice and policy. For example, more interpretable models need to be developed, multimodal data should be explored, and clinical studies should be conducted to validate the efficacy of these models.

Overall, this research work underscores the need for collaboration between healthcare professionals, researchers, and policymakers to develop and implement integrated intelligent computing models in a responsible and effective way to improve healthcare outcomes for children with cognitive-based neurological diseases.

6.2 Limitations and future research directions.

The paper identifies several limitations and future research scope.

One demerit of ML and DL models is the lack of interpretability which can be challenging for clinicians to understand and trust the results. Future studies should focus on producing more interpretable models which will give the clinicians better understanding of the underlying mechanisms of cognitive-based neurological diseases.

Another limitation is the reliance on single-modality data, such as brain imaging or language analysis, in current models. Future research should explore the use of multimodal data, such as combining brain imaging and language analysis, to enhance the reliability accuracy and robustness of models.

A third limitation is the lack of validation studies to test the efficacy of these models in clinical practice. Future research should include high amount of clinical data to validate the effectiveness of these models in improving the diagnosis and treatment of cognitive-based neurological diseases in children.

Finally, ethical and legal considerations need to be addressed when using intelligent computing models in healthcare. Future research should explore the development of guidelines and regulations to ensure patient privacy is protected, informed consent is obtained, and bias and fairness issues are addressed when using these models.

Overall, future research must concentrate on developing more interpretable and multimodal models, conducting clinical validation studies, and addressing ethical and legal considerations to ensure that integrated intelligent computing models can be effectively and responsibly used to improve healthcare outcomes for children with cognitive-based neurological diseases.

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